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ADAPTIVE FILTERING OF SEISMIC ARRAY DATA

ADVANCED ARRAY RESEARCH

Special Report No. 1

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ABSTRACT

Adaptive multichannel prediction filtering has been completed on four data samples, and adaptive maximum-likelihood signal extraction has been done on one sample.

Comparison of adaptive results with those obtained from processing the same data with stationary filters (nonchanging filters designed from correlation-function estimates) shows that the adaptive filters approach the stationary filters as k_s (the rate-of-convergence parameter in the adaptive algorithm) approaches 0. For larger values of k_s, adaptive prediction-error filtering does better than stationary filters on nontime-stationary data, but stationary filters are better on data samples which appear to be time-uniform.

The performance of an adaptively designed maximum-likelihood filter was shown to be essentially equivalent to that of a maximum-likelihood filter which was conventionally designed from correlation-function estimates.

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SECTION I

INTRODUCTION AND SUMMARY

This report presents initial results in a study of the adaptive filtering of seismic array data. There is a brief discussion of the theorectical basis of the adaptive algorithm and its application to multichannel prediction and maximum-likelihood filtering. Adaptive multichannel prediction filtering has been completed on four data samples, and maximum-likelihood signal extraction has been done on one sample. Adaptive filter results are compared with those obtained from stationary filters, i.e., from nonchanging filters designed from correlation function estimates.

Plots of both mean-square-error vs k_s (the rate-of-convergence parameter in the adaptive algorithm) and of mean-square-error vs time indicate that, in the limit as k_s approaches 0, the adaptive filters approach the stationary Wiener filters. For larger values of k_s, the mean-square-error of the adaptive prediction is found to be greater than the Wiener mean-square-error for some data samples and less for other samples. The data characteristic which defines the exact behavior of the mean-square-error-vs-k_s curve appears to be related to the time-stationarity of the data.

The performance of an adaptively designed maximum-likelihood filter was shown to be essentially equivalent to that of a maximum-likelihood filter which was conventionally designed from correlation-function estimates.

SECTION II
THEORY OF ADAPTIVE FILTERING

To derive the Widrow adaptive-filter algorithm without becoming too involved with notation, the simple problem of single-channel prediction will be used to illustrate the main features of the algorithm. Later, the algorithm will be expanded to the multichannel case; and its application to maximum-likelihood signal extraction will be discussed.

A. SINGLE-CHANNEL PREDICTION

Consider a single channel of sampled data points, x_i; and let the problem be to take p consecutive values of x_i and use them to predict the value of the next point. To do this, these values of x_i are considered to be components of a p-dimensional column vector,

$$\underline{X}_n = \left(x_{n-p+1},\ x_{n-p+2},\ x_{n-p+3},\ \ldots,\ x_n\right)^T \tag{2-1}$$

To predict the value of the next point, x_{n+1}, the scalar product is formed from the data vector $\underline{X}_n$ with the prediction-filter vector,

$$\underline{F} = \left(f_1,\ f_2,\ f_3,\ \ldots,\ f_p\right)^T \tag{2-2}$$

The error in the prediction of x_{n+1} is

$$\epsilon_{n+1} = x_{n+1} - \underline{F}^T\,\underline{X}_n \tag{2-3}$$

and the squared error is

$$\epsilon_{n+1}^2 = \underline{F}^T \underline{X}_n \underline{X}_n^T \underline{F} - 2\underline{F}^T \underline{X}_n x_{n+1} + x_{n+1}^2 \qquad (2\text{-}4)$$

The expected value of ϵ_{n+1}^2 is given by

$$\overline{\epsilon_{n+1}^2} = \underline{F}^T \overline{\underline{X}_n \underline{X}_n^T} \underline{F} - 2\underline{F}^T \overline{\underline{X}_n x_{n+1}} + \overline{x_{n+1}^2} \qquad (2\text{-}5)$$

Equation (2-5) shows the expected value of ϵ_{n+1}^2 to be representable as a dimensional quadratic surface in F. The value of F at which the minimum of the expected ϵ_{n+1}^2 surface occurs is the optimum filter in the least-squares sense. Adaptive processing starts with some arbitrary filter vector F and iteratively converges toward the optimum F. In this report, the $(n+1)^{th}$ iteration of F, F_{n+1} is found from F_n by the method of steepest descent, which can be summarized in the following two rules:

1) Move opposite the direction of the gradient of the $\overline{\epsilon_{n+1}^2}$ surface

2) The distance moved in this direction is proportional to the magnitude of the gradient, and the constant of proportionality is called k_s

Cast into equation form, these two rules yield the steepest-descent algorithm

$$\underline{F}_{n+1} = \underline{F}_n - k_s \nabla \overline{\epsilon_{n+1}^2} \qquad (2\text{-}6)$$

In practice, the gradient of the expected value of ϵ^2_{n+1} is not known. However, the Widrow adaptive-filter algorithm meets this problem by making the approximation

$$\nabla \overline{\epsilon^2_{n+1}} \approx \nabla \epsilon^2_{n+1}$$

$\nabla \epsilon^2_{n+1}$ is obtained by differentiating Equation (2-4) with respect to F^T, giving

$$\nabla \epsilon^2_{n+1} = 2\underline{X}_n \underline{X}_n^T \underline{F}_n - 2\underline{X}_n x_{n+1} = -2\epsilon_{n+1}\underline{X}_n \qquad (2\text{-}7)$$

Combining Equations (2-7) and (2-6) gives the Widrow single channel adaptive algorithm of

$$\underline{F}_{n+1} = \underline{F}_n + 2k_s \epsilon_{n+1} \underline{X}_n \qquad (2\text{-}8)$$

B. MULTICHANNEL PREDICTION FILTERING

The multichannel case is shown diagrammatically in Figure II-1. Here, C channels of time-series data are filtered by C digital filters to produce an output which is supposed to approximate y_n, the desired output. In this diagram, the subscript n used on the filter-column vectors, the input time-series data vectors, the desired output, and the prediction error indicates their values at the n^{th} time. The subscript is necessary on the filter vector since the filter weights change with time in the adaptive algorithm.

The derivation of the multichannel algorithm follows easily from the single-channel algorithm if a new column vector $\underline{X}'_n$ is made by placing the column vectors $X_n(i)$, i=1 to C, on top of each other and likewise forming a new column vector $\underline{F}'_n$ from the $\underline{F}_n(i)$, i=1 to C.

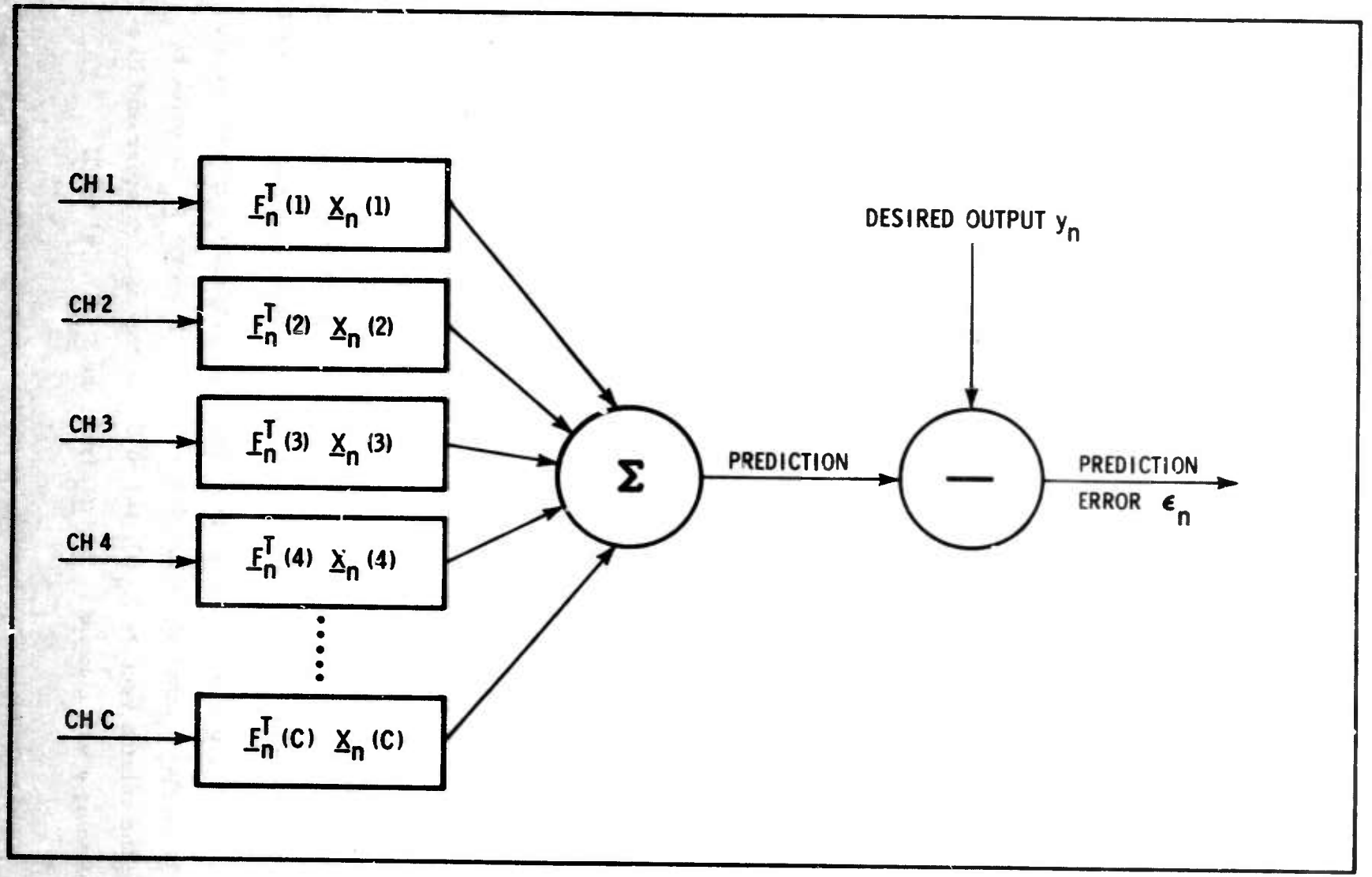

Figure II-1. Block Diagram of Multichannel Prediction Scheme

In terms of the new vectors, the prediction is given by a scalar product of $\underline{X}'_n$ and $\underline{F}'_n$. Thus the prediction error can be written as

$$\epsilon_n = y_n - \underline{F}'^{T}_n \underline{X}'_n \tag{2-9}$$

Using the same general procedure as used in deriving the single-channel algorithm, the multichannel adaptive-filter algorithm is then found to be

$$\underline{F}'_{n+1} = \underline{F}'_n + 2k_s \epsilon_n \underline{X}'_n \tag{2-10}$$

C. MAXIMUM-LIKELIHOOD SIGNAL EXTRACTION

The transformation of maximum-likelihood processing into problems of prediction is first considered. This transformation is desirable so that the adaptive-prediction method previously described can be used to design maximum-likelihood filters.

Suppose we have an N-channel problem and an L-point filter f_{ij}, where i=1, ..., N and j=1, ..., L. We wish to minimize the output of the filter

$$y_{t-s} = \sum_{ij} f_{ij} x_{i,t-j} \tag{2-11}$$

where $x_{i,t}$ is the output of seismometer i at time t. The criterion that y_{t-s} be an unbiased estimate at time t-s of the signal, which is assumed constant across channels, leads to the constraints

$$\sum_i f_{ij} = \delta_{js} \tag{2-12}$$

where

$$\delta_{js} = 0 \text{ for } j \neq s$$

and

$$\delta_{js} = 1 \text{ for } j = s$$

The constraints may be expressed as

$$f_{1j} = \delta_{js} - \sum_{i=2}^{N} f_{ij}$$

and substituted into Equation (2-11). This gives

$$y_{t-s} = \sum_{j} \left(\delta_{js} - \sum_{i=2}^{N} f_{ij} \right) x_{1,t-j} + \sum_{i=2}^{N} \sum_{j} f_{ij} x_{i,t-j}$$

which can be simplified to the form

$$y_{t-s} = x_{1,t-s} - \sum_{i=2}^{N} \sum_{j} f_{ij} \left(x_{1,t-j} - x_{i,t-j} \right) \qquad (2\text{-}13)$$

Referring to Equation (2-3), Equation (2-13) can be recognized as a prediction-error equation. Thus, the maximum-likelihood output y_{t-s} can be considered the error in predicting $x_{1,t-s}$ by filters operating on the set of data $(x_{1,t-j} - x_{i,t-j})$, where the filters are no longer subject to constraints.

Equations could now be written to specify the filters f_{ij} in terms of the covariances of the data $x_{i,t}$. These equations would be equivalent to the conventional system of equations but of order (N-1) L instead of NL. However, the purpose of this section is to determine adaptively the maximum-likelihood filters.

Referring to the algorithm of Equation (2-8) which resulted from Equation (2-3), an adaptive algorithm follows immediately from Equation (2-13). The resulting maximum-likelihood adaptive algorithm is

$$f_{ij}(t+1) = f_{ij}(t) + 2k_s y_{t-s} (x_{1,t-j} - x_{i,t-j}) \qquad (2\text{-}14)$$

The adaptive maximum-likelihood results in this report are derived by using Equation (2-14). Obviously, there are other ways of combining Equation (2-11) and the constraints of Equation (2-12) into a single prediction-error equation. For example, one could solve for f_{3j} and substitute into Equation (2-11), thereby predicting channel 3 from traces made by subtracting the remaining channels from channel 3. All of these different ways of producing a prediction-error equation are equivalent in the sense that the resulting equations specifying the filters in terms of the covariances of the data $x_{i,t}$ define equivalent filters. The adaptive algorithms resulting from the different prediction-error equations will be different, however.

All of these algorithms are determined by reducing the dimension of the problem by substituting in the constraint equation and then by finding the gradient for the reduced set of filter coefficients. The constraints are satisfied by actually using the projection of the subset gradient on the constraint plane. A better method is obtained by finding the gradient at a point in time for the complete set of coefficients and projecting this gradient on the constraint plane. This "full" gradient algorithm can be derived from Equations (2-11) and (2-12) by adding and subtracting

$$\sum_{ij} f_{ij} \bar{x}_{t-j}$$

where

$$\bar{x}_{t-j} = \frac{1}{N} \sum_{i=1}^{N} x_{i,\,t-j}$$

Thus,

$$y_{t-s} = \bar{x}_{t-s} - \sum_{ij} f_{ij} (\bar{x}_{t-j} - x_{i,\,t-j}) \qquad (2\text{-}15)$$

which is in the form of a prediction-error equation so that the corresponding adaptive algorithm is

$$f_{ij}(t+1) = f_{ij}(t) + 2k_s\, y_{t-s} (\bar{x}_{t-j} - x_{i,\,t-j}) \qquad (2\text{-}16)$$

Note that the constraints are always satisfied if the iteration is started with filters satisfying the constraints.

The final report will give a more complete description of maximum-likelihood processing by the adaptive method of Equation (2-16).

SECTION III
EXPERIMENTAL RESULTS

A. PREDICTION FILTERING

Adaptive multichannel prediction filtering has been completed on four data samples. Information about these data — which consist of UBO road noise, UBO normal noise, the center and first ring of LASA subarray B1, and 13 channels of array data — is given in Table III-1. These data samples also have been processed using Wiener prediction filters.

In the filtering program, the data in each trace are scaled by 1/(rms value of that trace) so that the variance of all data traces is 1. Thus, results of processing on the different data samples may be compared directly.

Results for each data sample are presented in the form of three figures. The first figure shows mean-square-error vs k_s and the Wiener filter mean-square-error. The second shows mean-square-error vs time for the Wiener filter, the adaptive filter with the large k_s, and the adaptive filter with the small k_s. It should be noted that the origin in these figures does not correspond to zero mean-square-error. The third figure is a plot of the channel to be predicted plus the prediction and prediction error of the Wiener and large and small k_s filters.

Power spectra of the channel being predicted and of the Wiener and adaptive error traces have been computed for UBO road noise and LASA subarray B1.

1. UBO Road Noise

A major highway passes within a few miles of the northwest extent of the UBO array. The UBO road noise (Figure III-1), which is predominantly Rayleigh energy believed to originate along this highway, does not arrive as a plane wavefront, is time varying, and is attenuated across the array.

Table III-1

SUMMARY OF DATA PROCESSED

Sample	Date	Time	Data Length After Resampling (points)	Data Length After Resampling (sec)	Number of Channels	Channels Used for Prediction	Channel Predicted	Filter Length	Number of Points Ahead Predicted
UBO road noise	9-23-64	16:06:20	1250	90	10	1 - 9	10	27	-13
UBO normal noise	9-30-64	21:51:10	1250	90	10	1 - 9	10	27	-13
LASA subarray B1 Center and first ring	3-25-66	04:26:43	2200	220	7	1 - 7	1	25	1
Array data	11-20-66	23:14:00	3250	234	13	2 - 13	1	37	-18
LASA subarray C1 First ring omitted (Maximum likelihood processing described in B)	11-10-65	03:48:28	3250	325	19	18 difference traces	1	21	0

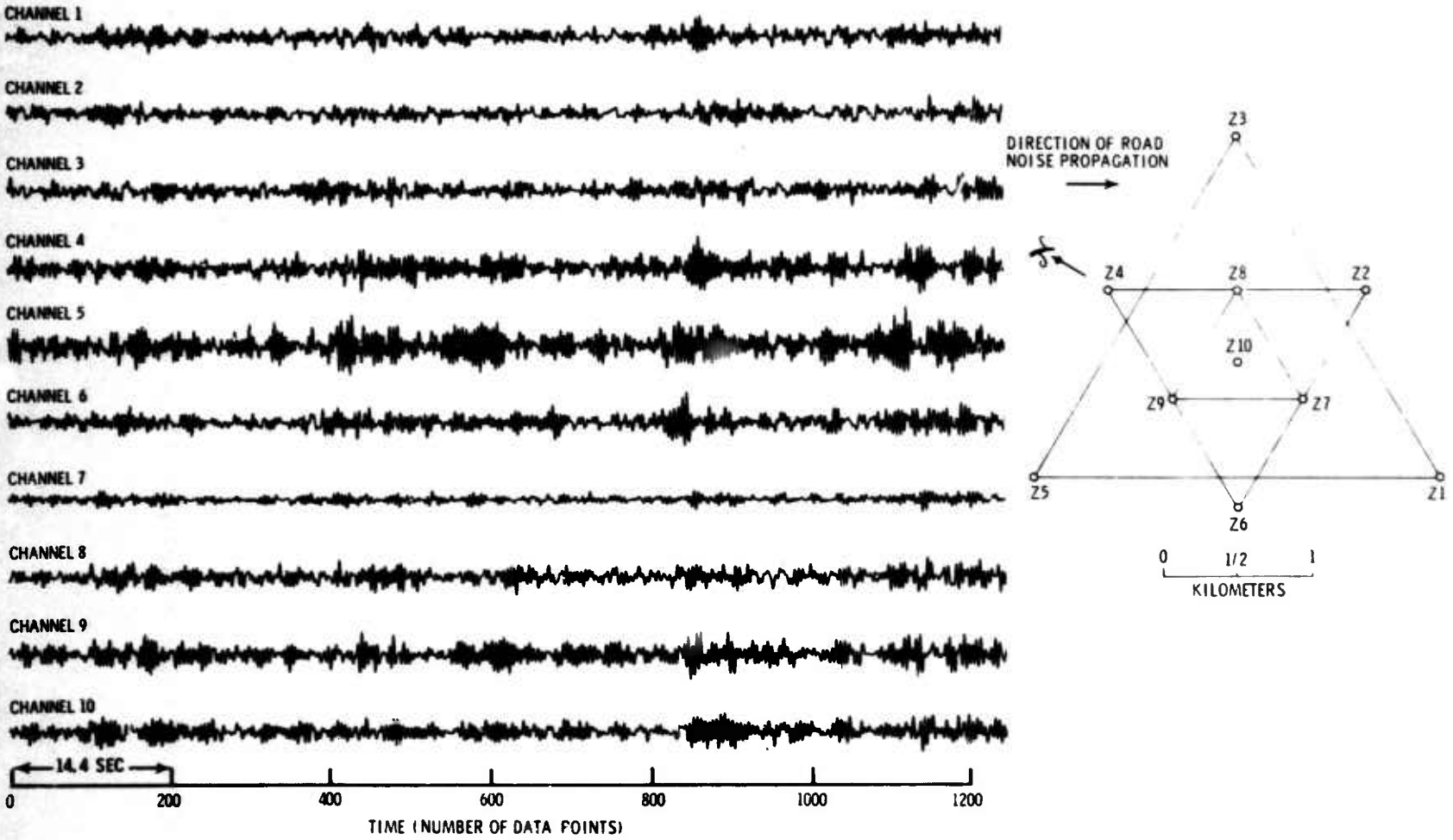

Figure III-1. Prefiltered and Resampled UBO Road Noise and UBO Array Geometry

Prior to any multichannel filtering, the data were prefiltered with an antialiasing, slightly prewhitening filter and resampled to a sample period of 72 msec.

A 27-point Wiener filter with its output point at the center of the filter had been designed previously[1] from these data to predict channel 10 using channels 1 through 9. The mean-square prediction error of the Wiener filter, when applied to the normalized design data, was 0.147.

Two adaptive processing runs, consisting of several passes through the data for each run, were made on this road-noise sample. At the beginning of the first pass of each run, the filter coefficients were set to 0; on successive passes, the coefficients initially were equal to their values at the end of the previous pass. The first run consisted of nine passes where k_s equaled 0.002 on the first pass and was scaled by two-thirds on each successive pass, ending with a value of 0.000117 after eight passes. For the ninth pass, k_s equaled 0.00005. In the second run, five passes were made, with k_s being equal to 0.0005 on the first pass; this was incremented by 0.0005 for each additional pass. Figure III-2 plots as a function of k_s the mean-square prediction error for each of these passes, excluding the first two in each run which were learning passes.

The fact that the adaptive filter does better than the Wiener filter for intermediate values of k_s is attributed to the nonstationarity of UBO road noise. Figure III-3 shows mean-square-error over 50-point intervals as a function of location in the data sample. The Wiener and small k_s adaptive plots are similar, while the plot for the strongly adapting filter appears to be independent of the others. This result supports the hypothesis that UBO road noise is highly nonstationary.

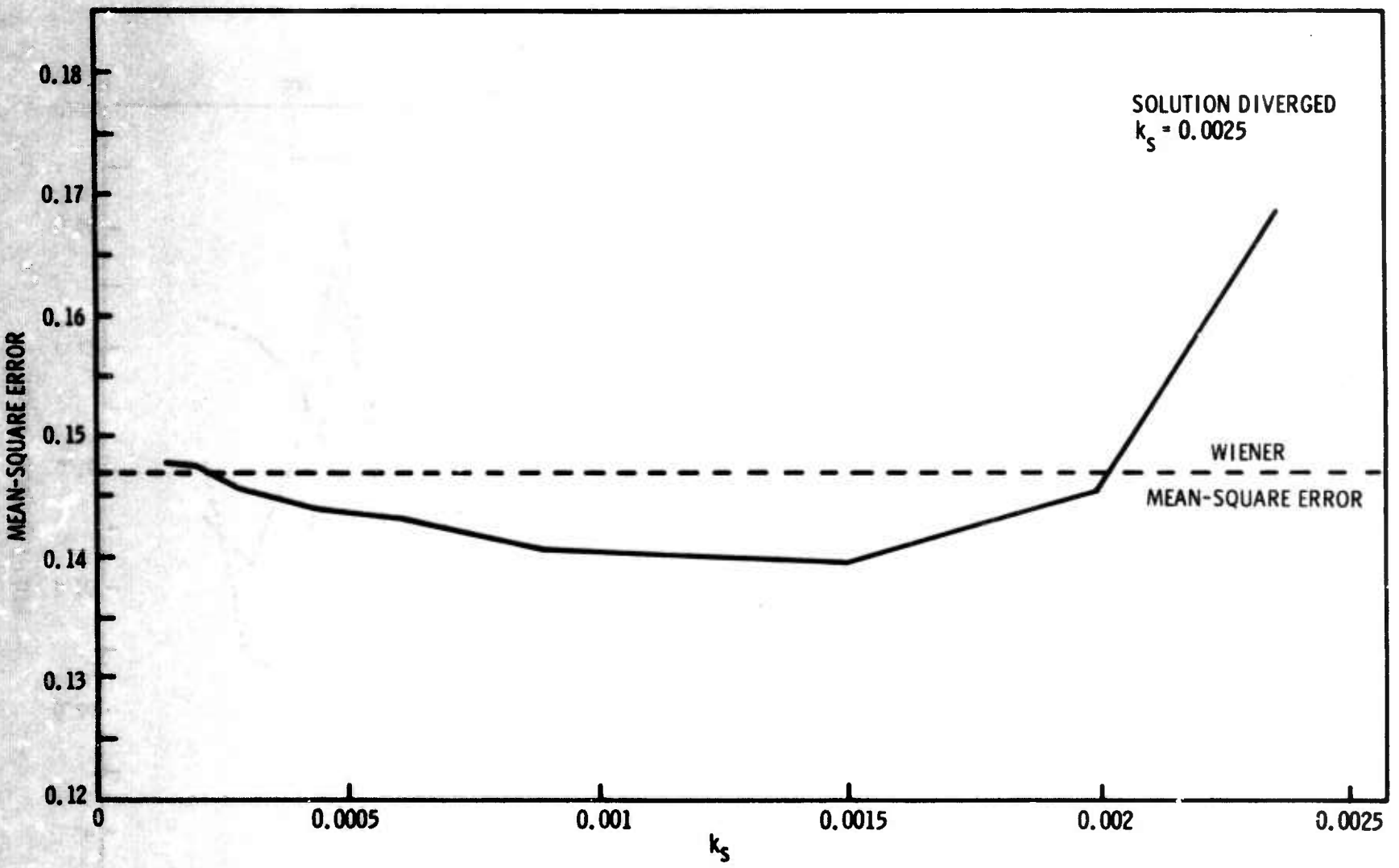

Figure III-2. UBO Road Noise, Mean-Square-Error Vs k_s

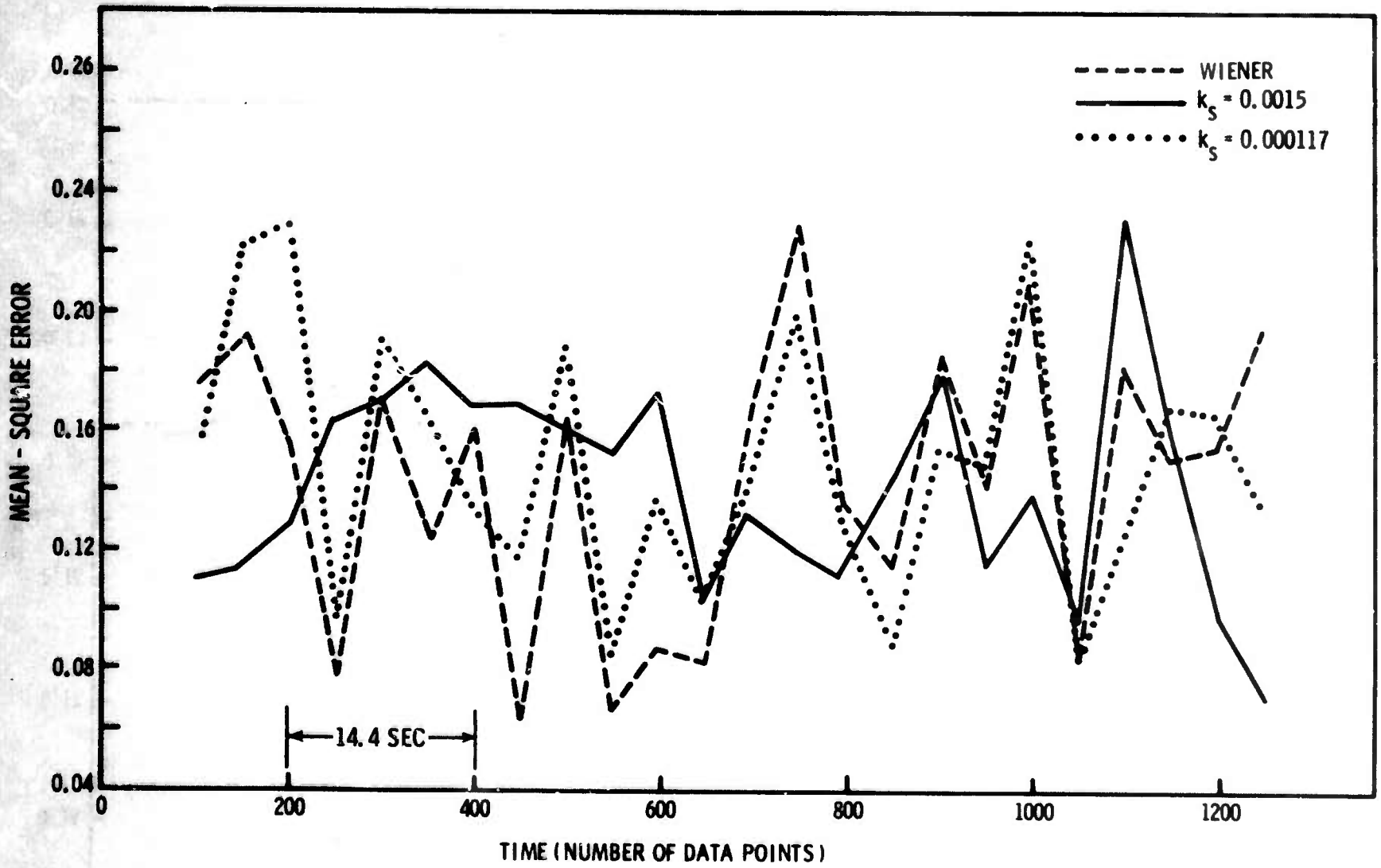

Figure III-3. UBO Road Noise, Mean-Square-Error Vs Time

Figure III-4 shows the energy of the power spectrum of channel 10 to be concentrated around 2.5 cps. The 2.5-cps peak is reduced least by the Wiener filter and is reduced most by the $k_s = 0.0015$ filter, with the $k_s = 0.00005$ filter falling between. Additional evidence of the nonstationarity of the data is the dissimilarity between the Wiener and the $k_s = 0.0015$ error spectra.

Figure III-5 shows channel 10 (the channel being predicted) as well as the prediction and prediction error for the Wiener and small and large k_s filters.

2. UBO Normal Noise

A sample of UBO data, called normal noise because it appears to travel across the array as unattenuated plane waves, is shown in Figure III-6. The UBO normal-noise sample was prefiltered, resampled, normalized, and Wiener-filtered with the same procedures used for the UBO road noise. The normalized mean-square prediction error of the Wiener filter was 0.28.

Three adaptive processing runs were made, one with eight passes and two with one pass with the filter weights being initially set to 0 at the beginning of each run. For the eight passes, k_s had the values of 0.0015 (learning), 0.0015, 0.001, 0.0005, 0.00025, 0.000125, 0.00005, and 0.002. Values of k_s for the second and third runs were 0.0025 and 0.003, respectively. Figure III-7 shows the mean-square-error from all runs (except the first learning pass).

The mean-square-error - vs - k_s curve for these data differs from the corresponding curve for road noise. Mean-square-error increases with increasing k_s up to approximately $k_s = 0.001$ and decreases with increasing k_s from $k_s = 0.001$ to 0.0025. Mean-square-error increases above $k_s = 0.0025$ where the algorithm becomes unstable.

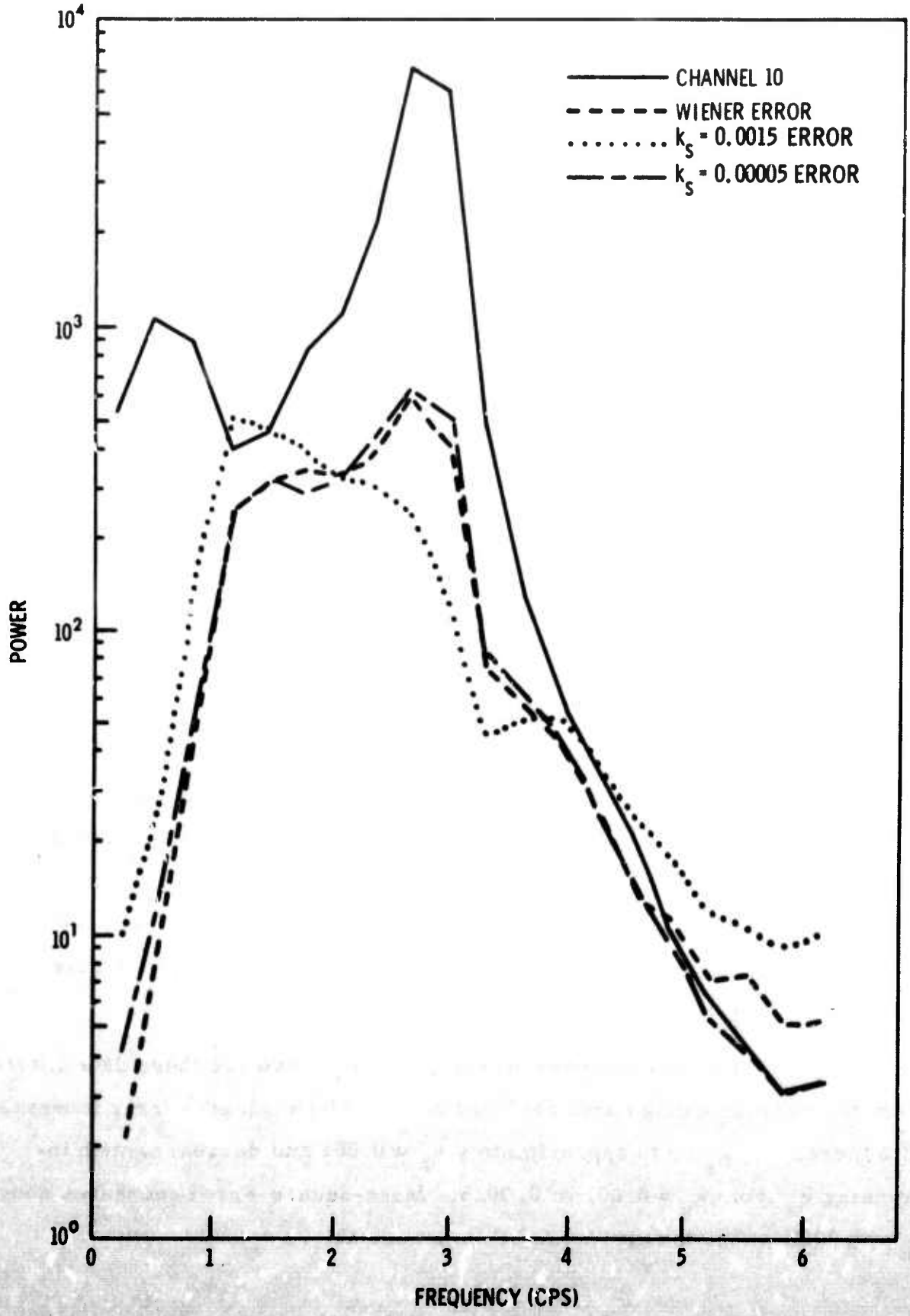

Figure III-4. UBO Road Noise, Power Spectra of Channel 10, Wiener Error, and Adaptive Errors

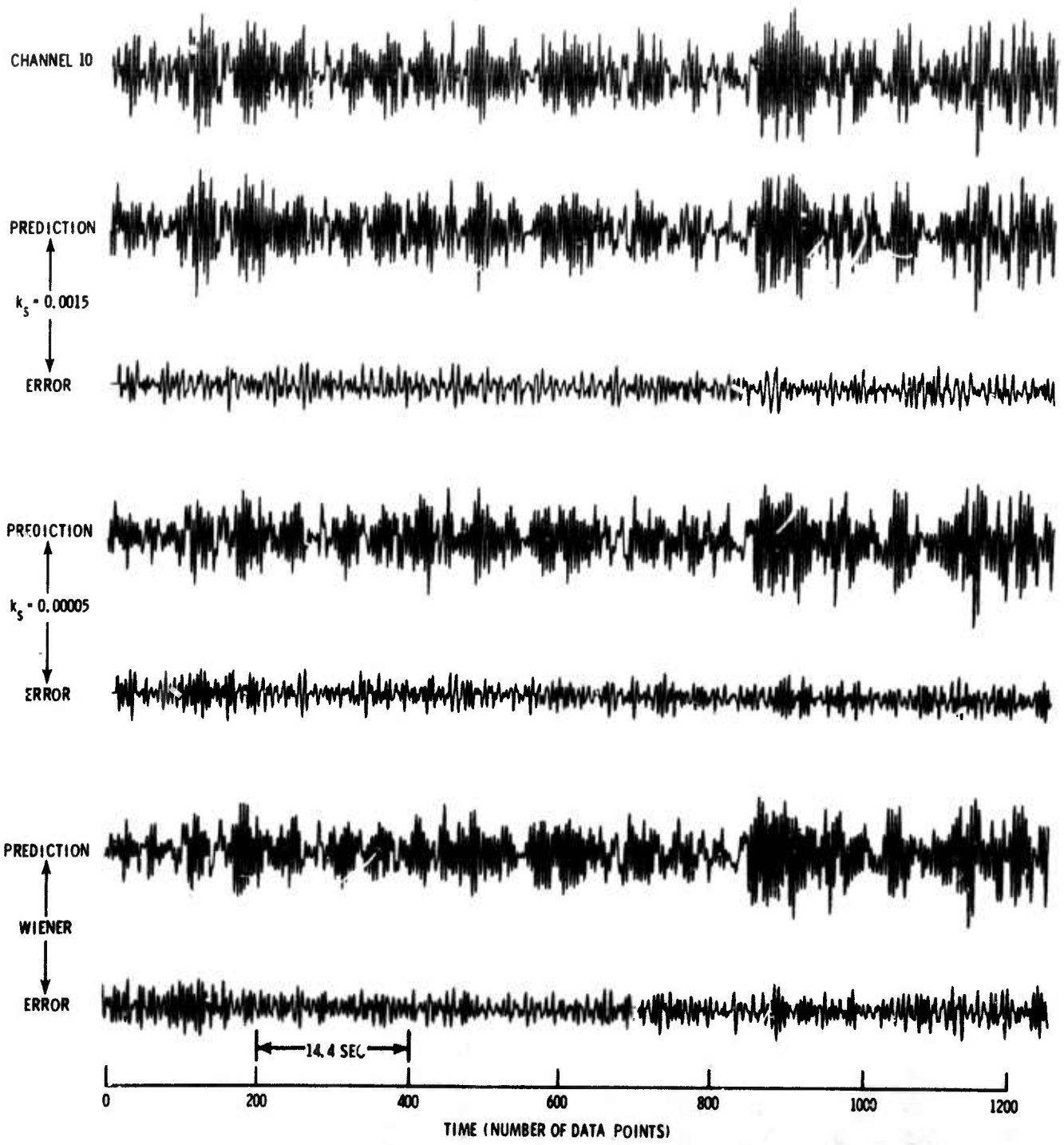

Figure III-5. UBO Road Noise, Wiener and Adaptive Filter Outputs

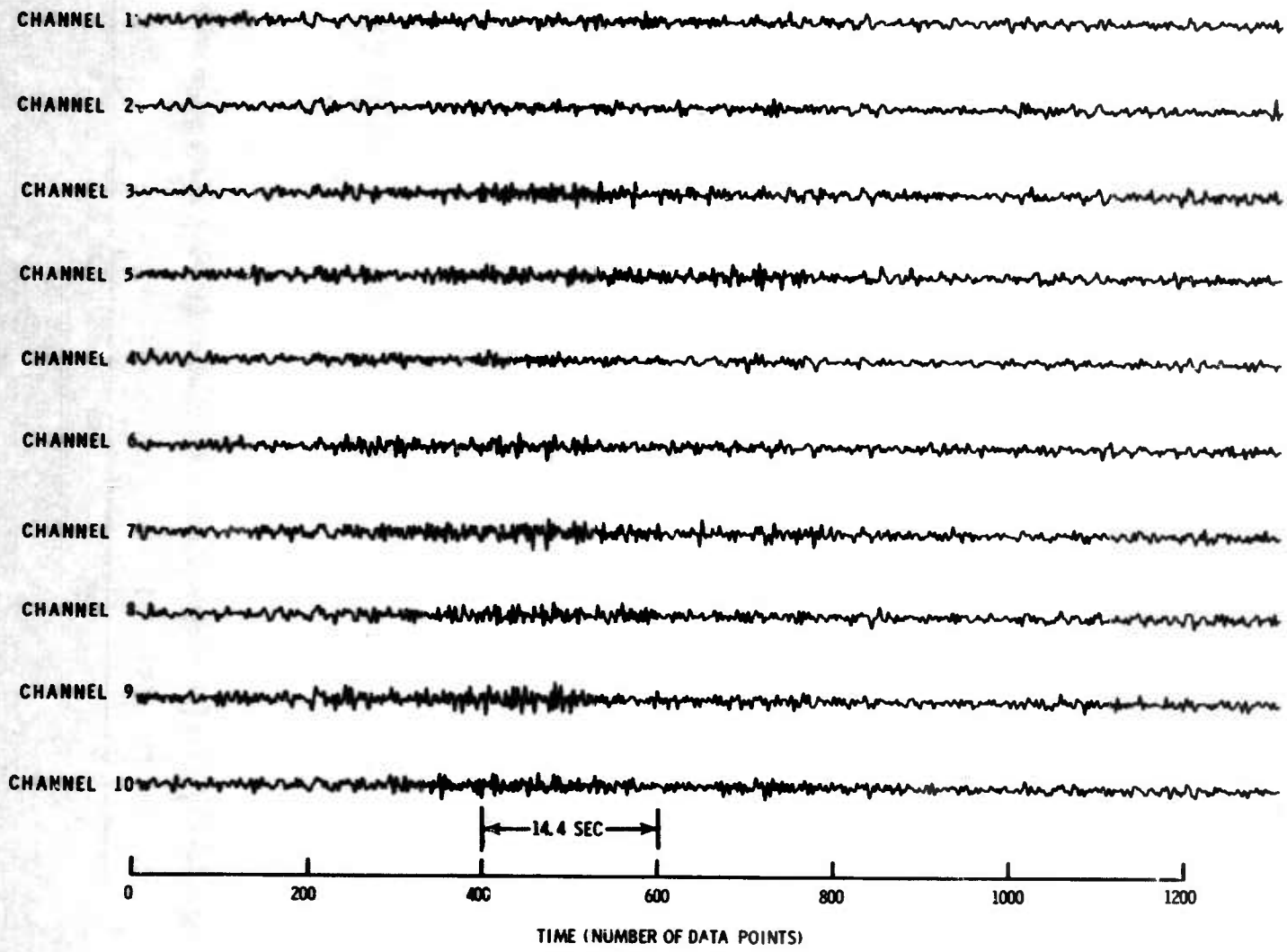

Figure III-6. Prefiltered and Resampled UBO Normal Noise

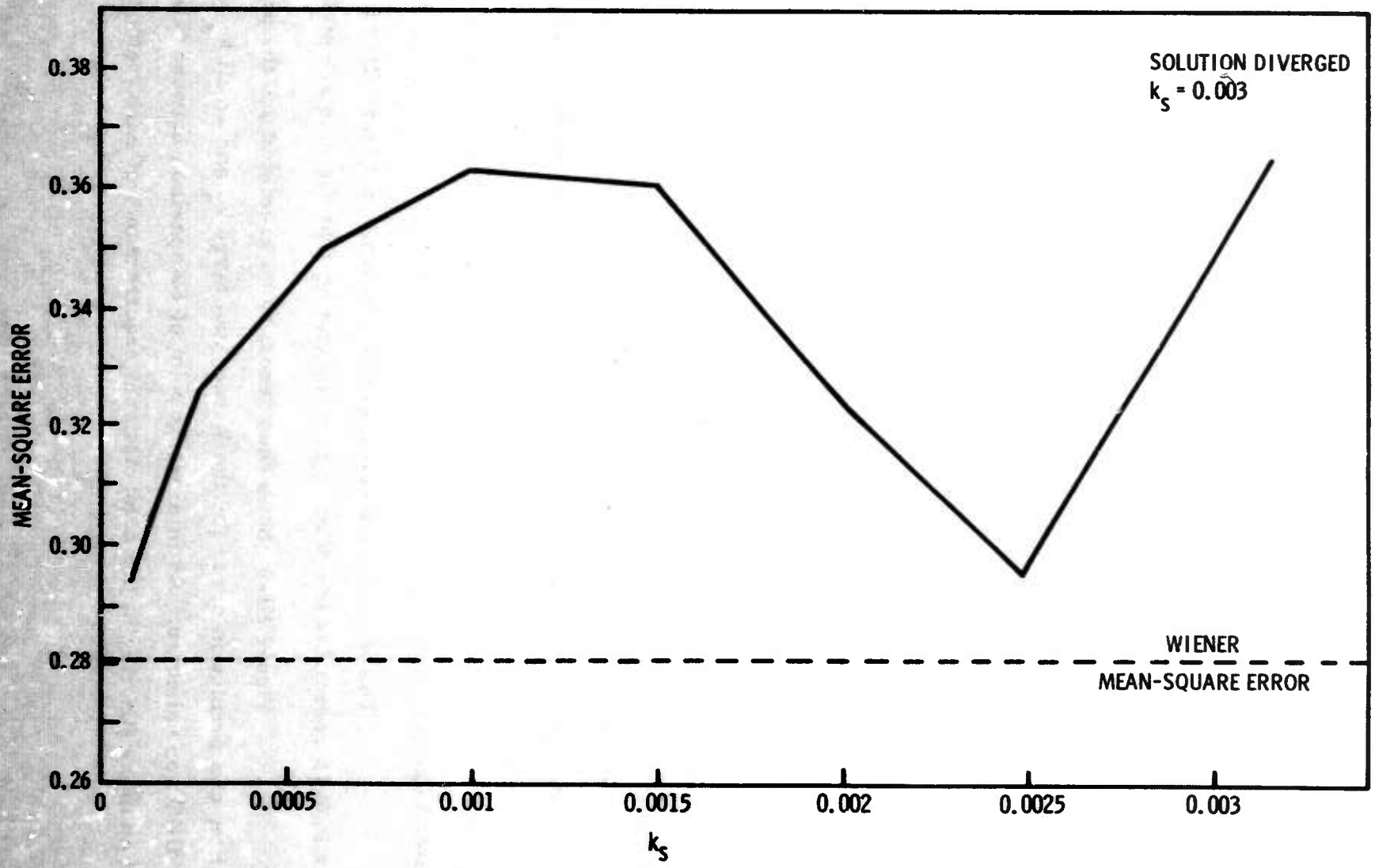

Figure III-7. UBO Normal Noise, Mean-Square-Error Vs k_s

Increasing mean-square-error with increasing k_s is the expected result for time-stationary data, since a larger k_s corresponds to a smaller time constant. Thus, the effective length of the data used in designing the filter is decreased, which means statistically that the misdesign and MSE of the filter are increased.

The dip in the MSE at $k_s = 0.0025$ in Figure III-7 is surprising. One possible explanation for this phenomenon is that the data are time varying, with a time constant which matches the adaptive time constant corresponding to $k_s = 0.0025$. This is probably not the correct reason for the dip since a similar effect is seen in other MSE-vs-k_s curves (Figures III-11 and III-16). A more likely explanation is that this decrease in mean-square-error is a false-gain effect caused by the narrow frequency bandwidth of the data. The second interpretation is based on the fact that a data point in a narrowband time series can be well predicted using the recent past of the trace. At first glance, this observation does not appear to apply because only data from channels 1 through 9 are used to predict channel 10. However, the adaptive filter, by means of the error term in the adaptive algorithm, is influenced by the channel 10 data values. Thus, indirectly, the adaptive-filter prediction does use the immediate past of channel 10, with the immediate past being more emphasized for larger values of k_s. This phenomenon will be discussed further in a later report.

The plot of mean-square-error vs time in Figure III-8 for $k_s = 0.0015$ resembles the Wiener plot, indicating that the data are stationary.

Figure III-9 shows the channel to be predicted and the prediction and prediction error for the Wiener and large k_s and small k_s cases for UBO normal noise. An interesting point of comparison between Wiener and adaptive filtering is the computational requirements of each method.

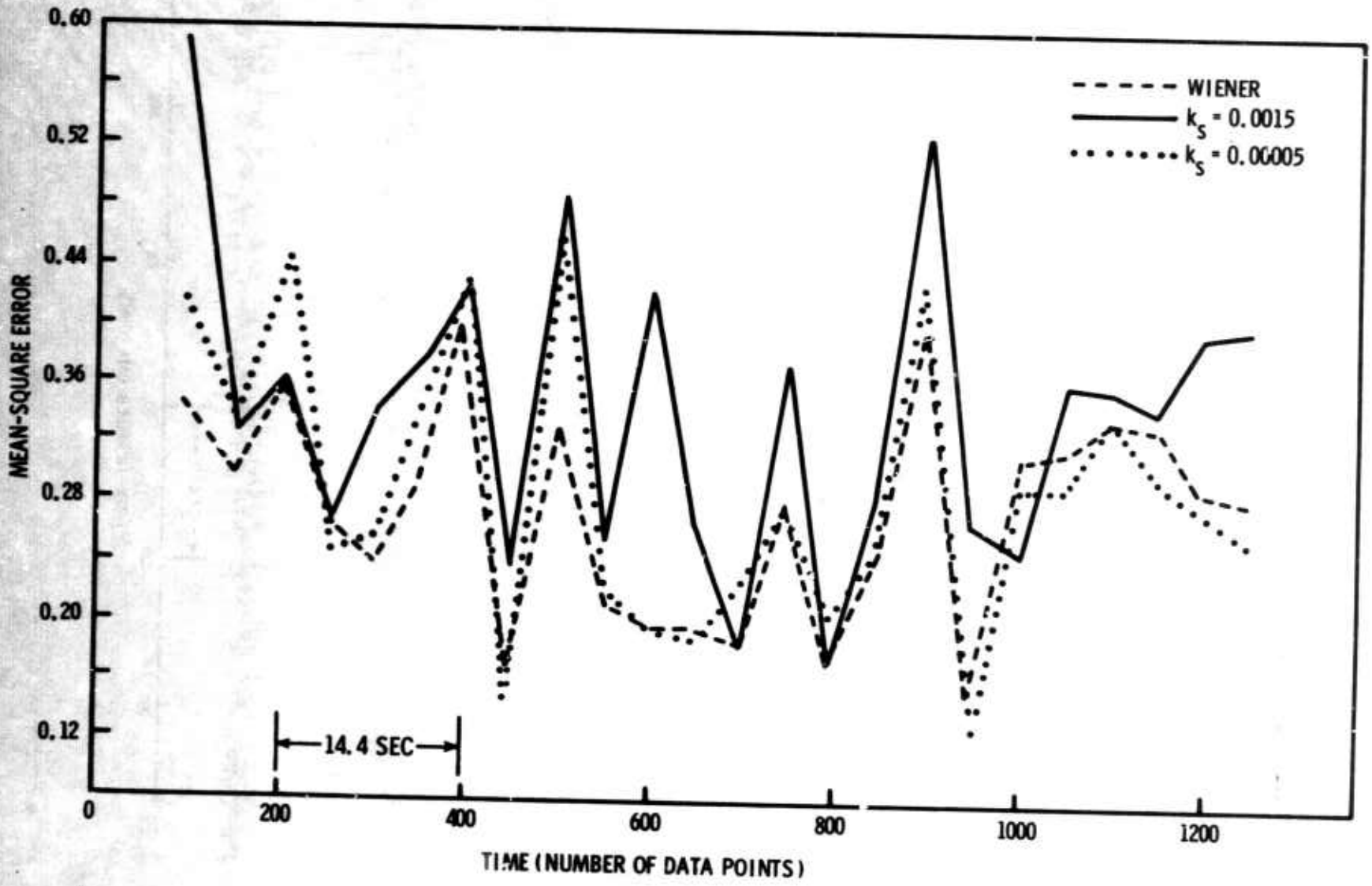

Figure III-8. Normal Noise, Mean-Square-Error Vs Time

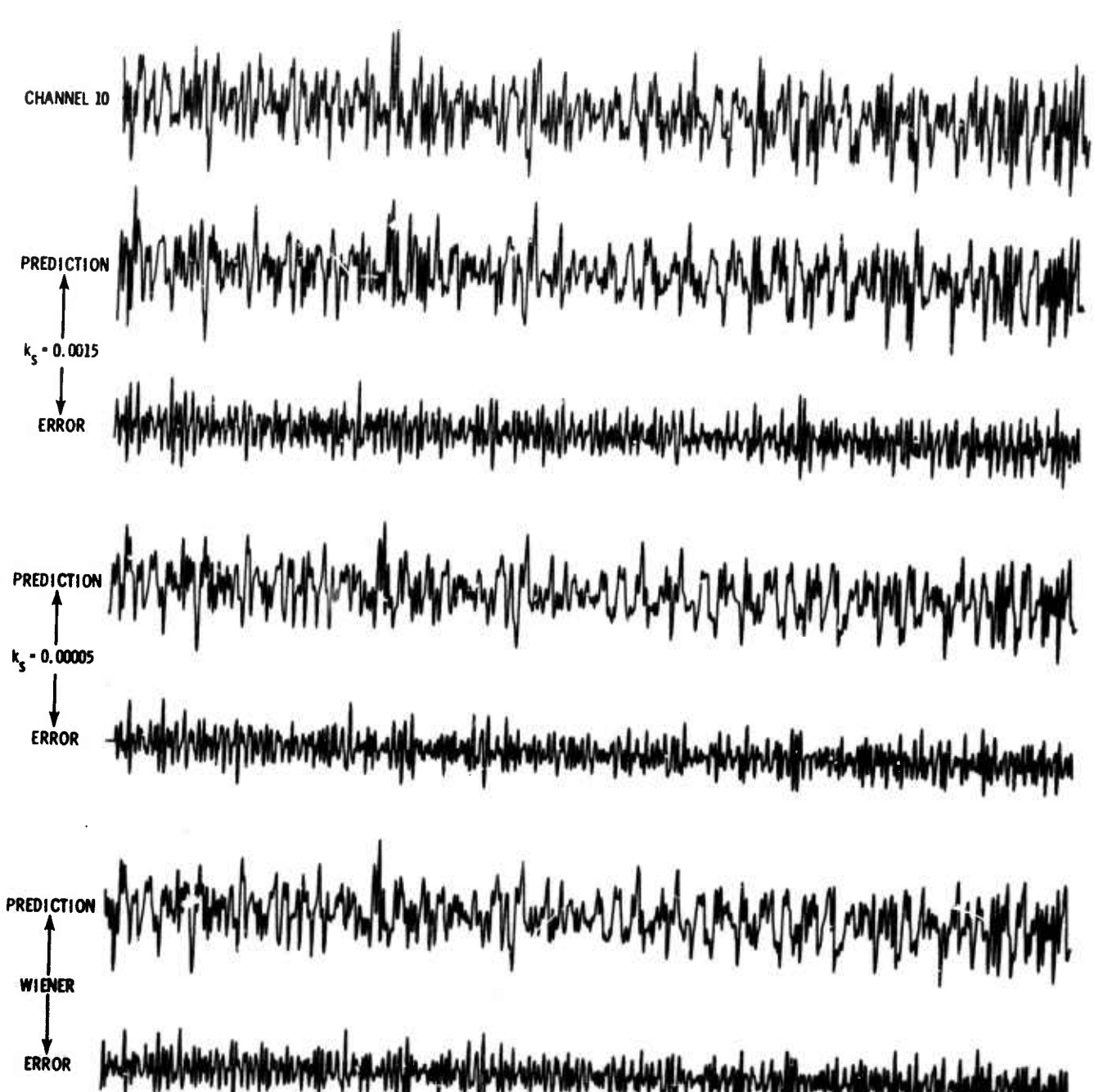

Figure III-9. UBO Normal Noise, Wiener and Adaptive Filter Outputs

On the IBM 7044, the total time to design and apply the Wiener filters to UBO normal noise was 30 min. The procedure involved five separate runs. One run of three adaptive passes through the data would require less than 9 min and would result in approximately the same filters.

3. LASA Subarray B1

Another data set used the center seismometer and the first ring of LASA subarray B1. The data shown in Figure III-10 have been antialias-filtered and resampled to a sample rate of 100 msec. Wiener filters, 20-points long, were designed to predict one point ahead on channel 1 based on channels 1 through 7. The resulting normalized mean-square-error was 0.031.

One adaptive filtering run of eight passes was made on these data with k_s values of 0.0015 (learning), 0.0015, 0.001, 0.0005, 0.00025, 0.000175, 0.0001, 0.00005, and 0.002. The mean-square-error - vs - k_s curve (Figure III-11) resulting from the adaptive filtering of these data has the same concave-downward shape as seen for UBO normal noise. The plot for $k_s = 0.001$ (Figure III-12) resembles the $k_s = 0.00005$ curve enough that the data can be considered time-stationary, although not to the extent of the UBO normal noise. The question of a concave-upward or concave-downward shape for the mean-square-error - vs - k_s curve apparently involves the time-stationarity of the data.

The power spectrum of channel 1 (Figure III-13) shows no dominant high frequency as is the case for UBO road noise. The similarity in the spectra of the $k_s = 0.001$ error and the $k_s = 0.00005$ error is further indication of the stationarity of this data sample.

Figure III-14 shows the Wiener and adaptive filtering results for this LASA data set.

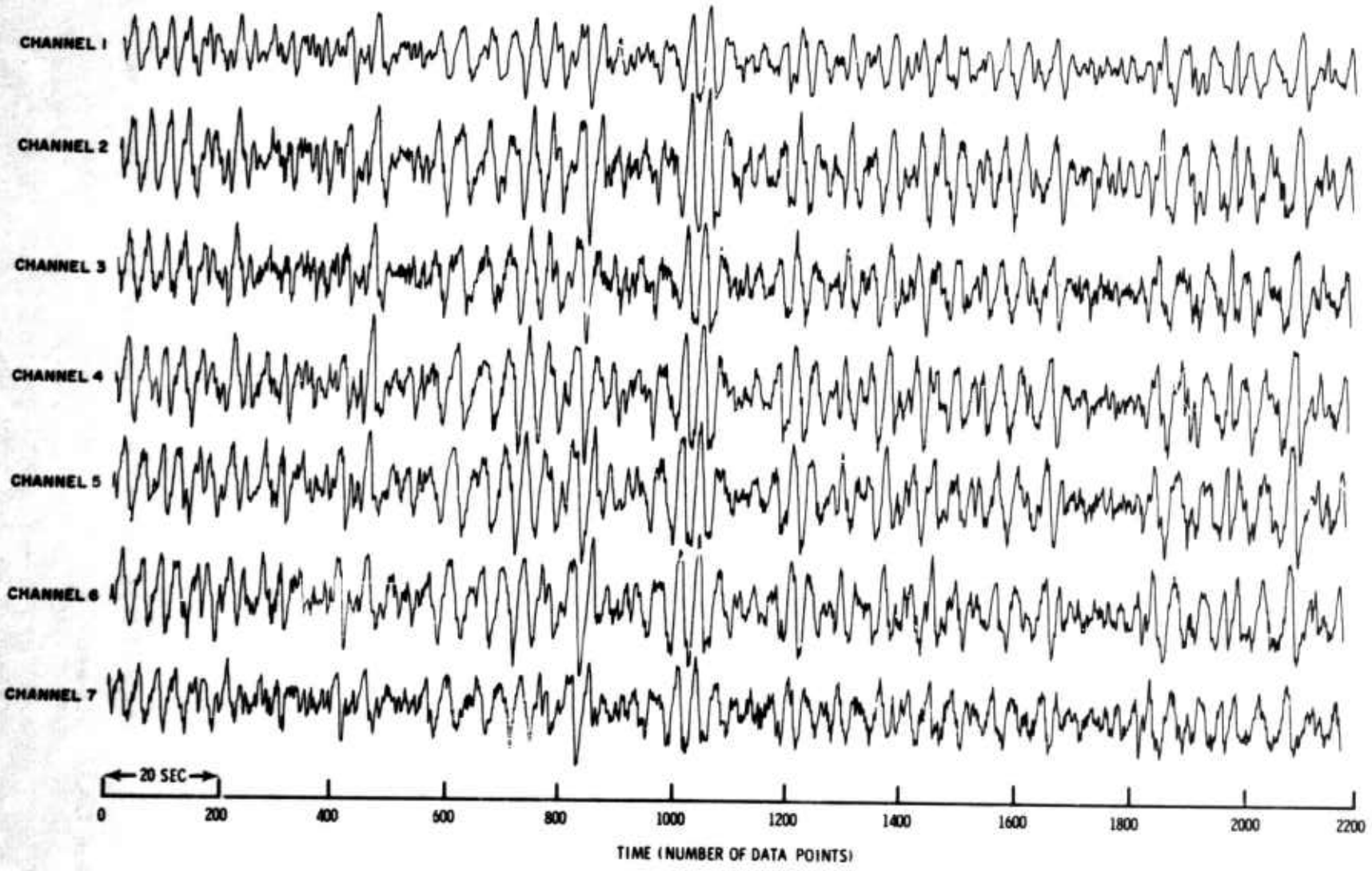

Figure III-10. LASA Subarray B1 Center Seismometer and First Ring Prefiltered and Resampled

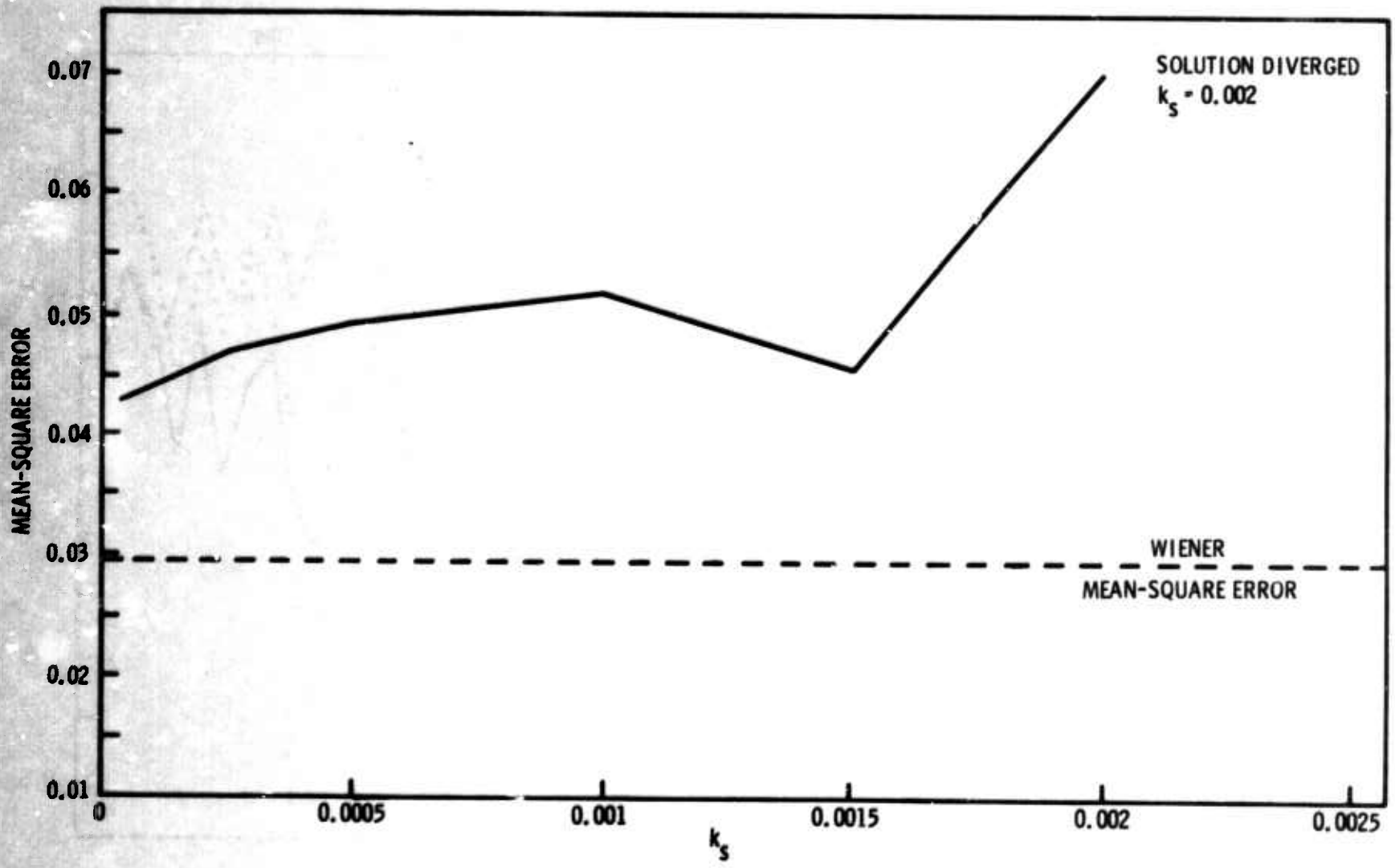

Figure III-11. LASA Subarray B1 Center Seismometer and First Ring, Mean-Square-Error Vs k_s

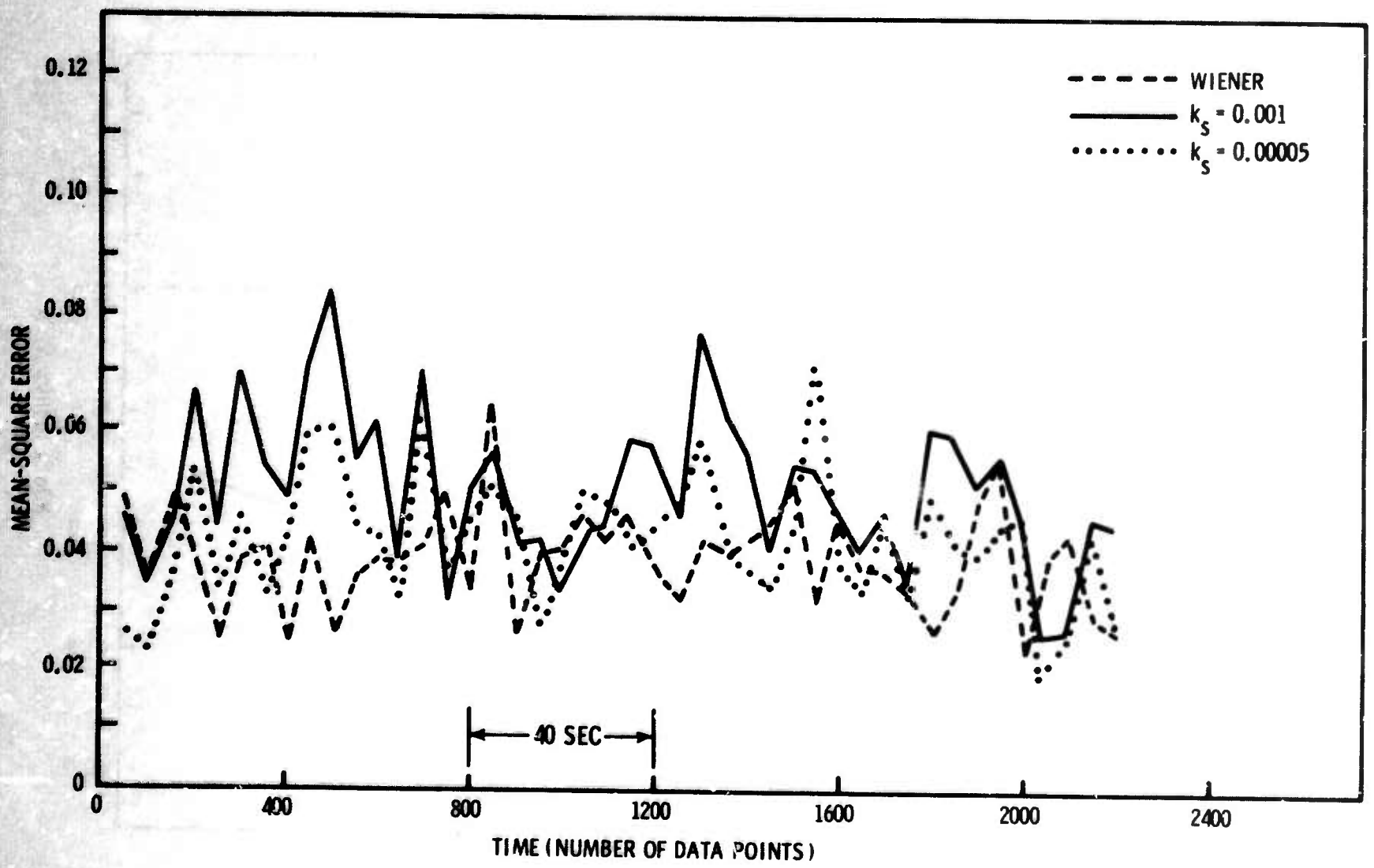

Figure III-12. LASA Subarray B1 Center Seismometer and First Ring, Mean-Square-Error Vs Time

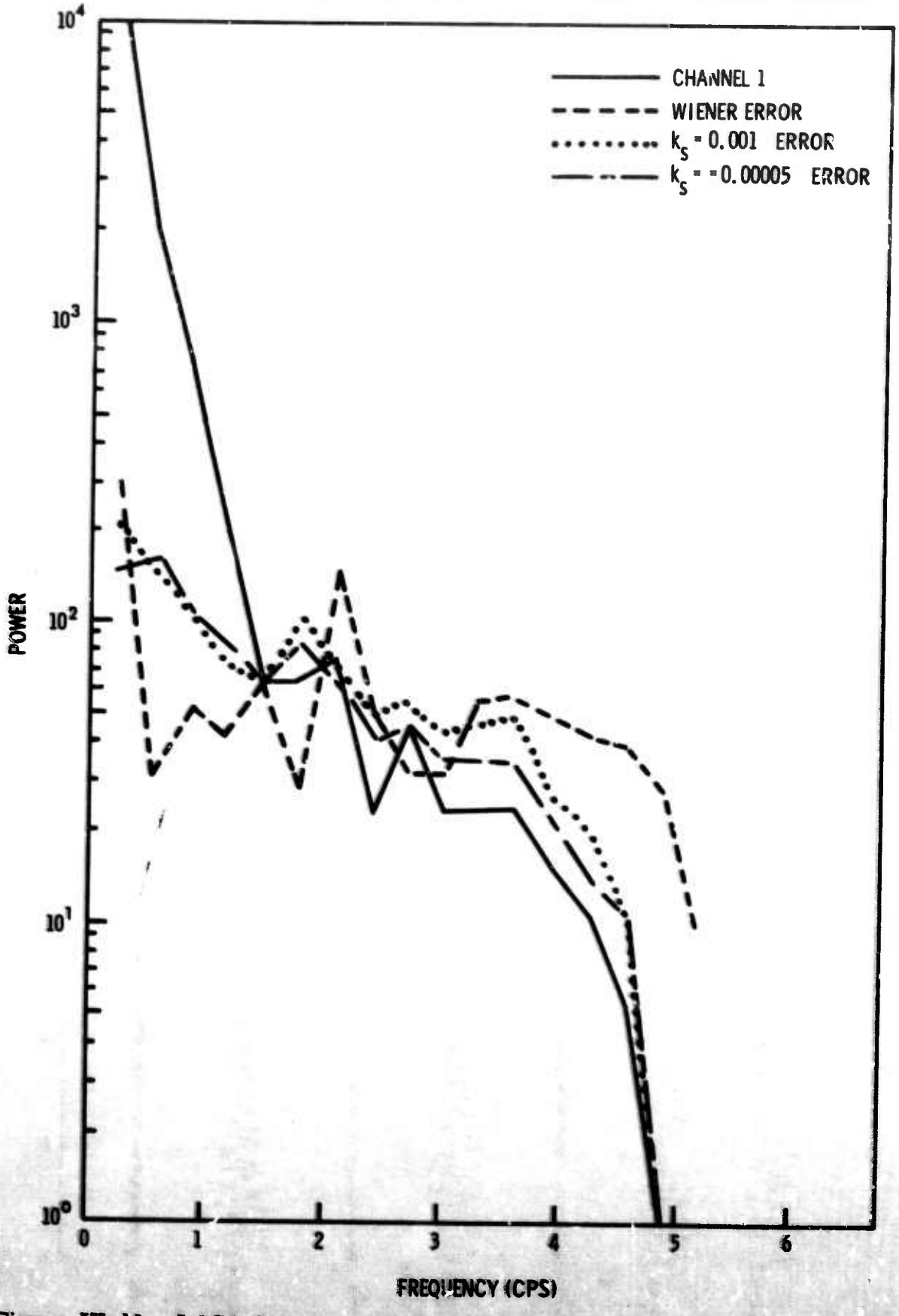

Figure III-13. LASA Subarray B1 Center Seismometer and First Ring — Power Spectra of Channel 1, Wiener Error, and Adaptive Errors

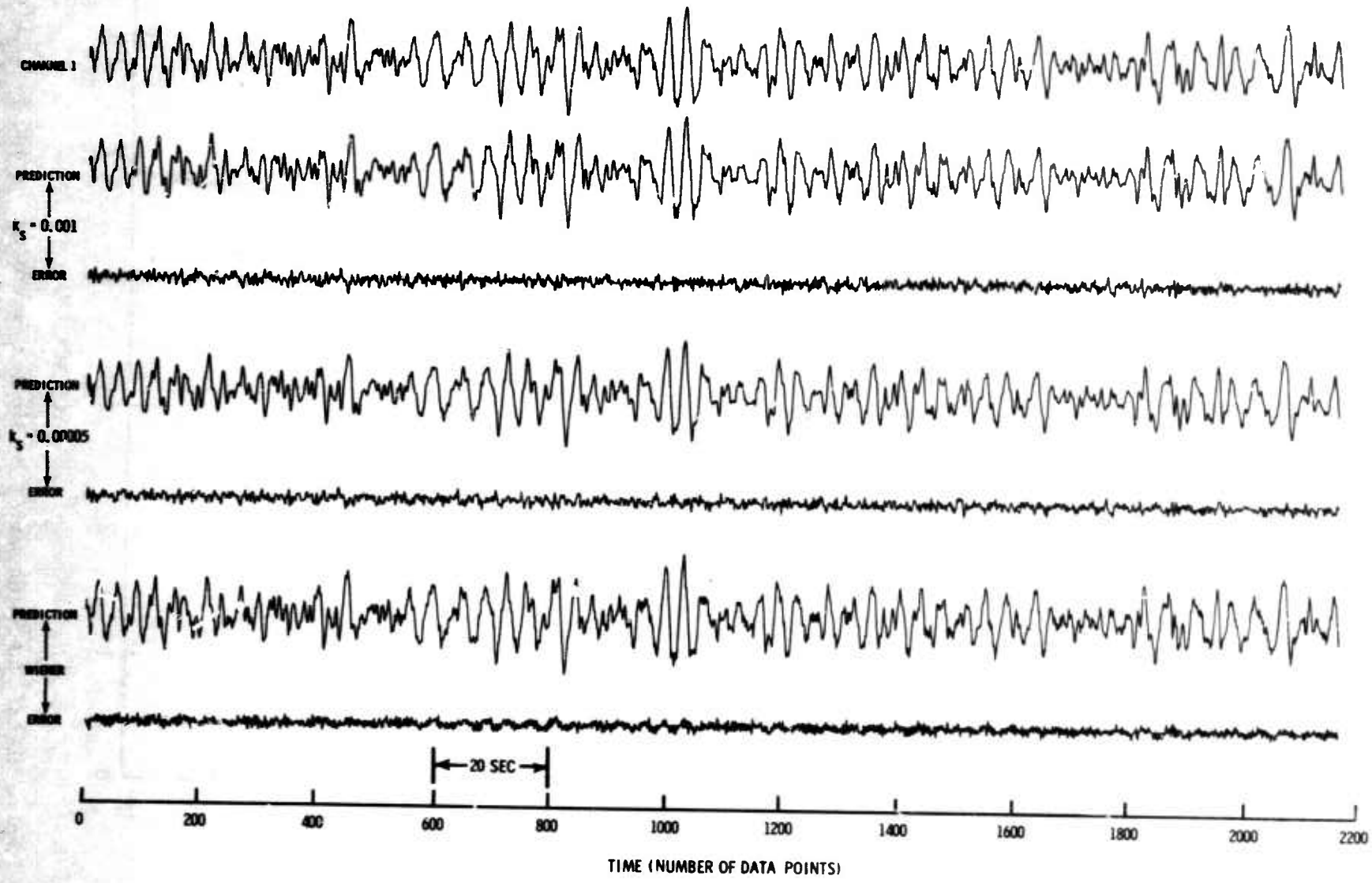

Figure III-14. LASA Subarray B1 Center Seismometer and First Ring, Wiener and Adaptive Filter Outputs

4. Array Data

The 13 channels of array data shown in Figure III-15 have been prewhitened and resampled. A 37-point Wiener filter, with output point at the center, was designed for these data to predict channel 1 from channels 2 through 13. The resulting normalized mean-square-error was 0.16.

Starting with the filter weights set to 0, one adaptive-filtering run having six passes with k_s values of 0.0005 (learning), 0.0005, 0.00025, 0.000125, 0.00005, and 0.00075 was made on these data. Figure III-16 shows intermediate values of k_s resulting in errors smaller than the Wiener mean-square-error. In Figure III-17, the dissimilarity between the Wiener and the $k_s = 0.0005$ plots, especially in the first part of the data, indicates that the data are nontime-stationary. (The behavior of the UBO road noise was the same and was also nontime-stationary.)

Figure III-18 shows the predictions, the prediction error, and the channel to be predicted for the Wiener and large k_s and small k_s filters.

B. MAXIMUM-LIKELIHOOD FILTERING

To compare adaptive maximum-likelihood filtering with conventional maximum-likelihood filtering, the same basic multichannel data used by SDL in their conventional maximum-likelihood study[2] were used for our adaptive maximum-likelihood work. These data, which came from LASA subarray C1, consisted of 19 of the possible 25 subarray channels, the six seismometers in the inner ring being omitted. A 3250-point, 100-msec sampling-period data segment, which included the signal arrival from an Aleutian Islands event, was the common data. The time traces were prepared by first filtering them with a 0.8- to 2.8-cps bandpass filter, which was thought to be the same as in the SDL study, and then time-shifting them to align the signal.

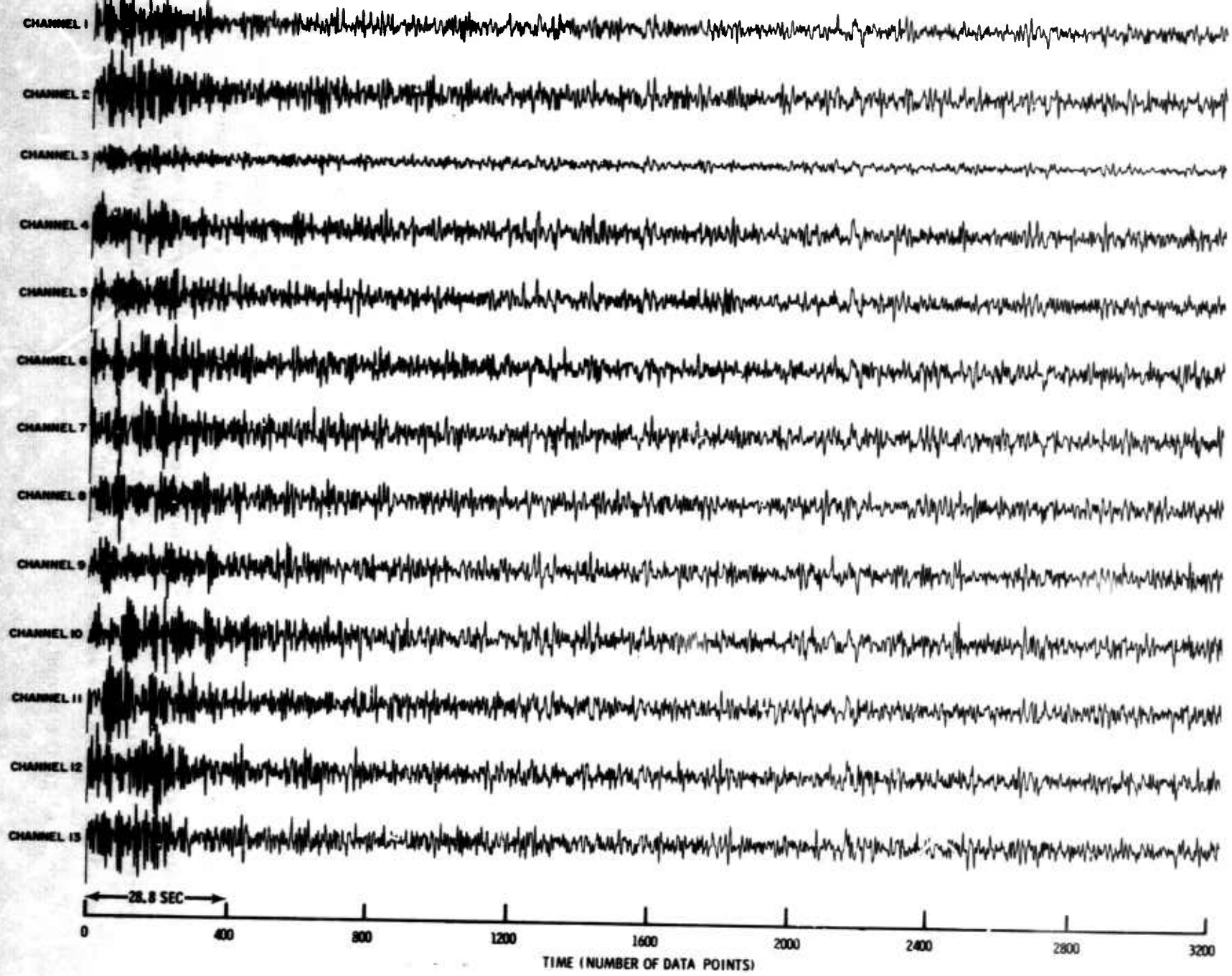

Figure III-15. Prefiltered and Resampled Array Data

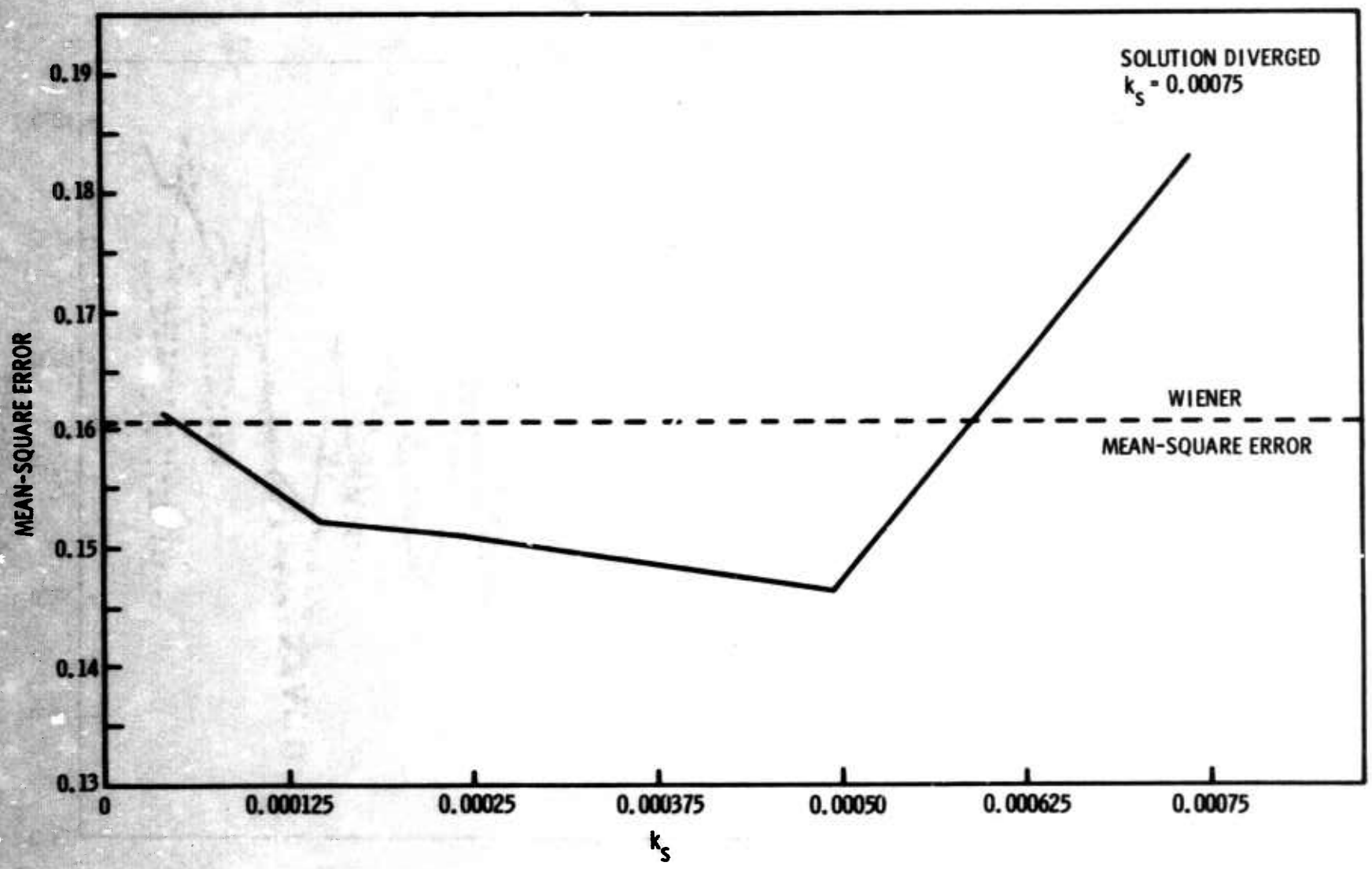

Figure III-16. Array Data, Mean-Square-Error Vs k_s

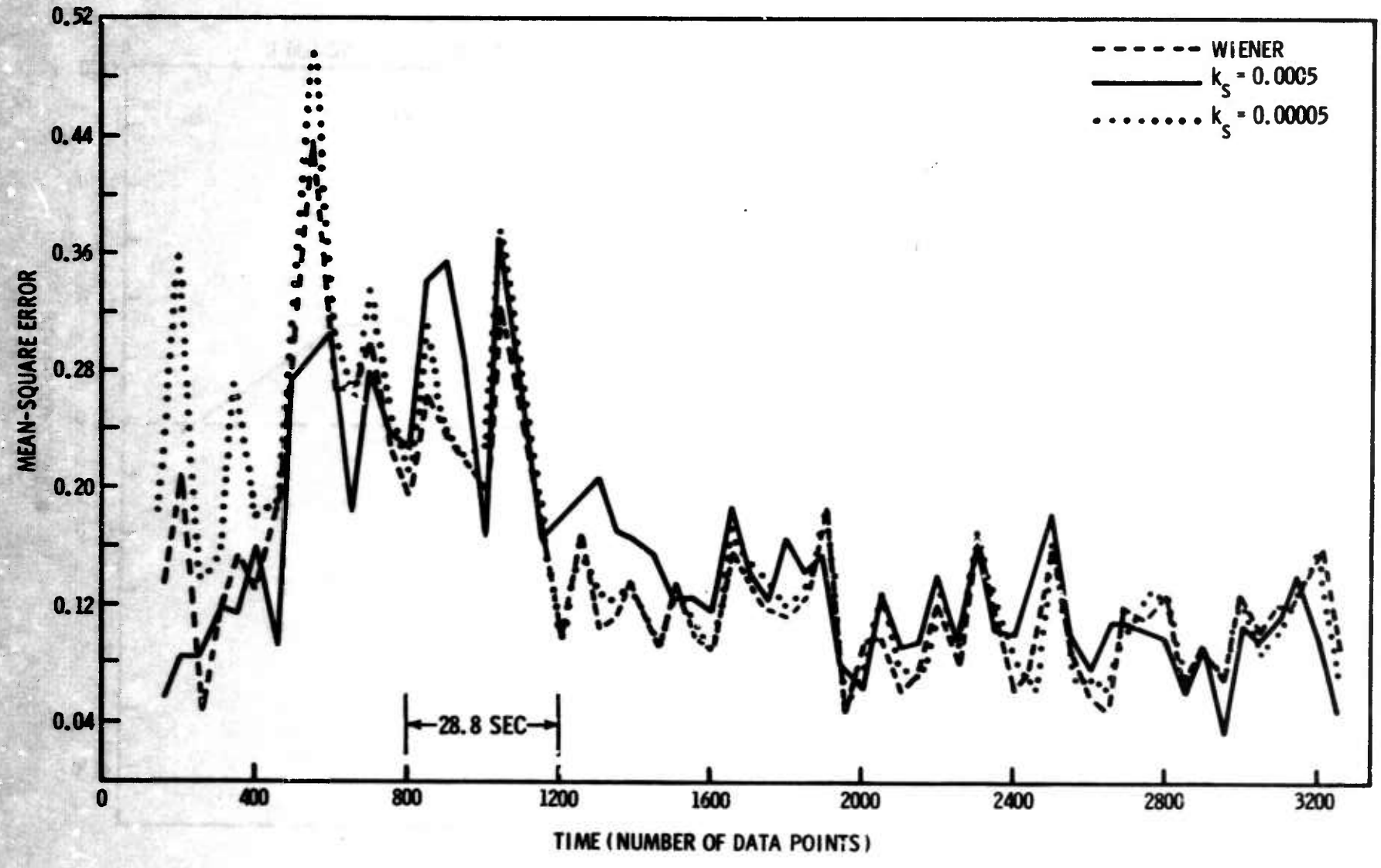

Figure III-17. Array Data, Mean-Square-Error Vs Time

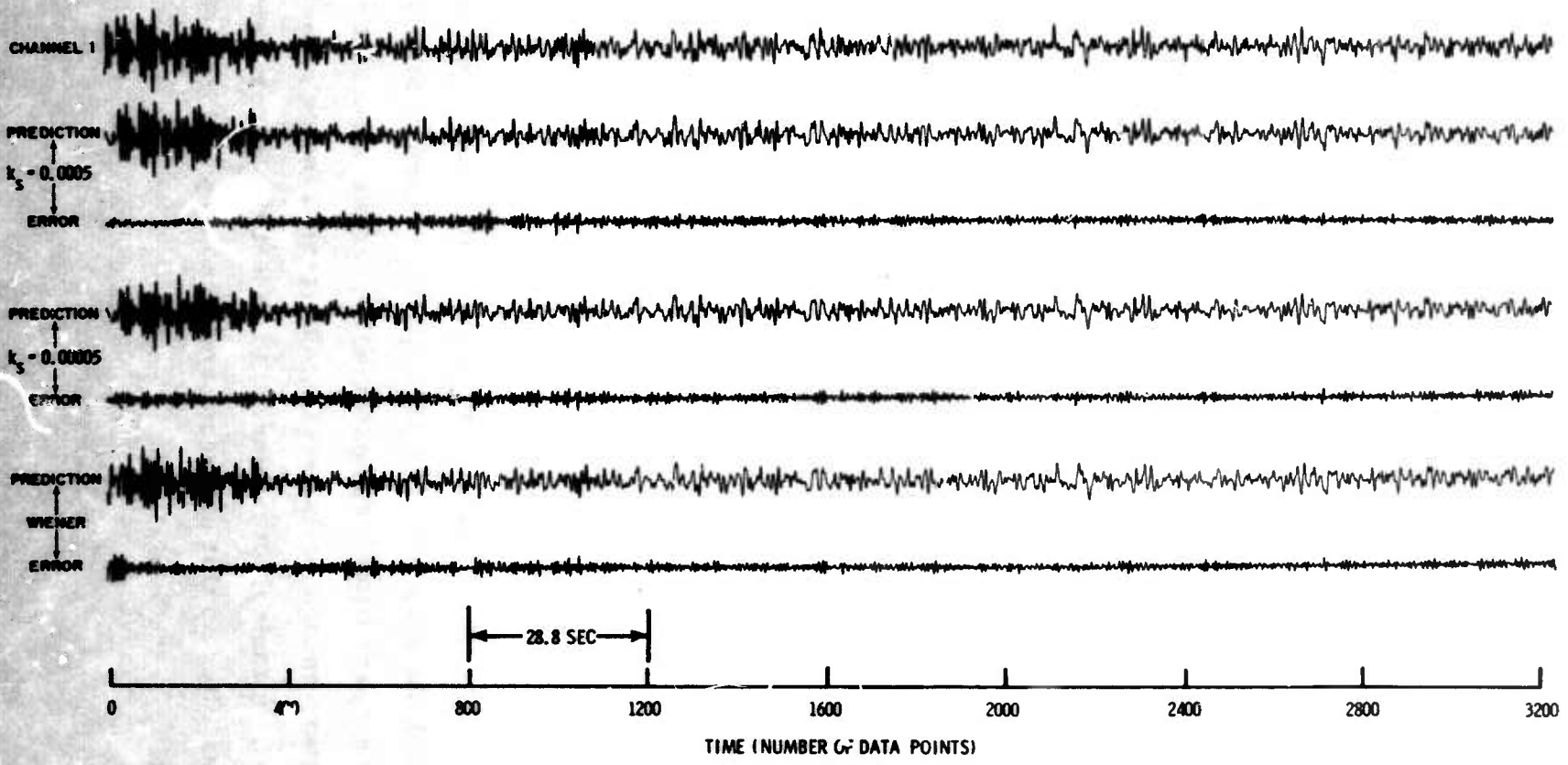

Figure III-18. Array Data, Wiener and Adaptive Filter Outputs

To form a prediction problem, traces 2 through 19 were subtracted from channel 1, yielding 18 difference traces that were normalized and used to predict channel 1, which was also normalized to a variance of 1.

One-sided, 21-point adaptive maximum-likelihood filters, similar to the SDL filters, were designed by two methods. The first, beginning with the filter weights set to 0, included three passes through the data interval from 750 to 2250 points, starting with $k_s = 0.0005$ for the first pass and using decreasing values of k_s (0.00025, 0.00005) for each successive pass. At the end of the third pass, the filters were fixed and the entire data sample was filtered with these fixed filters. The SDL conventionally designed maximum-likelihood filter used the same 750- to 2250-point filtering interval. The second method began with filter weights of 0, used a k_s of 0.00005, and let the filters operate on-line (i.e., adapt and filter) for one pass through the data.

Figure III-19 shows the outputs of a phased sum, the conventional maximum-likelihood filter, and the two types of adaptive maximum-likelihood filters. As can be seen, the adaptively designed fixed filter is essentially equivalent in performance to that of the SDL-designed filter. The on-line filter, which had been adapting for 1725 points at the beginning of the shown trace, is about 3-db poorer than the off-line filters.

It was planned to have a quantitative comparison of the SDL filter with the adaptively designed filter. However, the frequency response of our bandpass filter was appreciably narrower than that of the SDL bandpass filter, enough so that measured signal-to-noise ratio improvements have little meaning. It is planned to repeat this experiment using the SDL bandpass filter so that our results can be compared in a more precise manner.

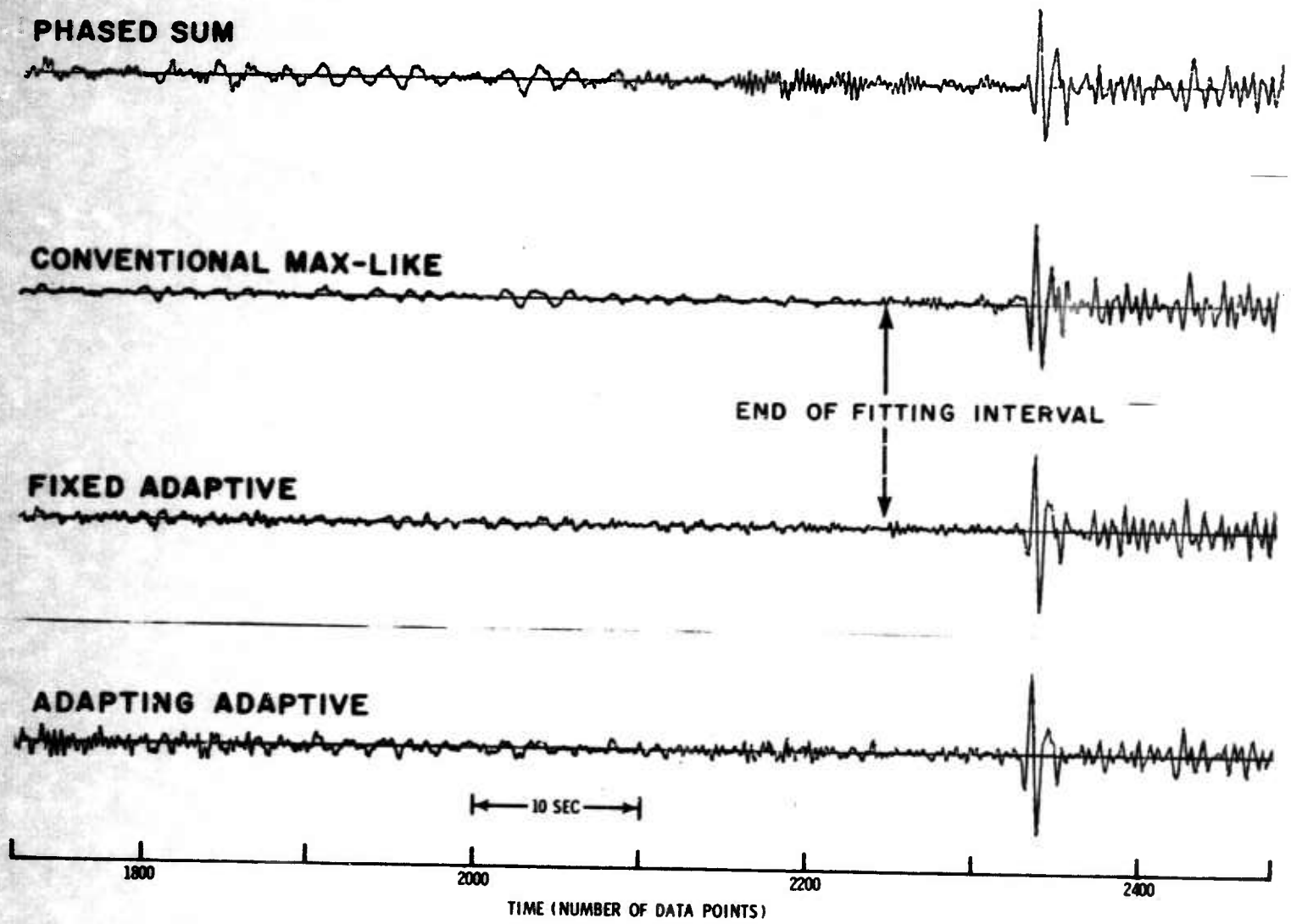

Figure III-19. Maximum-Likelihood Filter Outputs

SECTION IV
CONCLUSIONS AND RECOMMENDATIONS

From the theory of adaptive filtering, adaptive prediction filtering results would be expected to show several things. The adaptive filter should approach the Wiener filter as k_s approaches 0. This convergence, which was not explicitly searched for, seems to be true experimentally.

Another expected result is that the adaptive mean-square-error may be less than the Wiener mean-square-error if the data are time-varying but should always be greater if the data are stationary. The excess mean-square-error for stationary data can be shown to result from random oscillations of the filter coefficients about their optimum values.[3] Smaller adaptive mean-square-errors for nonstationary data are produced by the ability of the filters to track the changing minimum of the quadratic error-squared surface. These theoretical expectations seem to be verified in general by our experimental results. The exception is the interesting phenomenon of the dip in mean-square-error for large values of k_s (just before the algorithm becomes unstable). This MSE decrease, which is thought to be false gain caused by the narrow frequency bandwidth of the data, is a subject for future study. The final expected theoretical result is that, as k_s increases, a point is reached where the algorithm becomes unstable. A study of the parameters controlling the stability of the algorithm is being made.

The following summarizes our conclusions and recommendations.

- Results of this study indicate that, in the limit as k_s approaches 0, the resulting adaptive filter approaches the Wiener filter; therefore, the adaptive processing scheme could be of value as an economical means of Wiener filter design

- As data statistics change, the optimum value of k_s changes; therefore, the investigation of methods of varying k_s with changing data statistics is recommended

- Some data samples, when filtered adaptively, result in concave-downward mean-square-error-vs-k_s curves while other data samples result in a concave-upward curve; preliminary results given in this report indicate that the data characteristic which determines the shape of this curve is related to the time-stationarity of the data

- Adaptive maximum-likelihood filtering results indicate that this type of filtering can be done with much less time and expense than required by conventional means

- The inclusion of methods of extending the adaptive filtering concepts to the problem of signal extraction based on a theoretical signal model is recommended for any future study

- Only one prewhitened sample is included in the data processed here; the other three samples will be prewhitened and adaptively filtered by the same procedure used on the raw data in this report in order to determine the effects of prewhitening on adaptive filtering, and a later report will present these results

SECTION V

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2. Teledyne, Inc., 1966: Two Examples of Maximum-Likelihood Filtering of LASA Seismograms, Contract AF 33(657)-15919, 8 Jun.

3. Stanford Electronics Laboratories, 1966: Adaptive Filters I: Fundamentals, Tech. Rpt. No. 6764-6, Contract DA-01-021 AMC-90015(Y), Dec.

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13. ABSTRACT

Adaptive multichannel prediction filtering has been completed on four data samples, and adaptive maximum-likelihood signal extraction has been done on one sample. Comparison of adaptive results with those obtained from processing the same data with stationary filters (nonchanging filters designed from correlation-function estimates) shows that the adaptive filters approach the stationary filters as k_s (the rate-of-convergence parameter in the adaptive algorithm) approaches 0. For larger values of k_s, adaptive prediction-error filtering does better than stationary filters on nontime-stationary data, but stationary filters are better on data samples which appear to be time-uniform. The performance of an adaptively designed maximum-likelihood filter was shown to be essentially equivalent to that of a maximum-likelihood filter which was conventionally designed from correlation-function estimates.

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